Aalto University
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Effect of attention on returns of initial public offerings

Study of Twitter as a measure of attention

Bachelor's Thesis

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Abstract

Findings show that during the week before initial public offering date the number of tweets mentioning the ticker of the firm increases significantly compared to previous weeks. The increase in tweets has a significant positive correlation with IPO first day performance. If stock faces upward price pressure not based on fundamentals, it should do worse in the long term and the increase in tweets before IPO also shows a significant negative effect on long term performance of stock during the year after IPO. These findings support the hypothesis that attention leads to short-term overperformance and long-term underperformance. This shows that number of tweets for Twitter can be used as a measure of attention in context of IPOs. In the end I propose two different strategies on when to take part in an IPO based on the change in Twitter mentions.

Keywords Attention, Initial public offering, IPO, Twitter

Contents

1. Introduction

Odean (1999) proposed that individual investors invest only in stocks that they pay attention to and therefore measuring the attention could be used in predicting price movements. Barber and Odean (2007) later found that individual investors do not really take short positions, so attention should lead to upward price pressure. This pressure based on attention makes the price higher than fundamentals would state and therefore rational investors should bring it back to intrinsic value meaning long term negative abnormal returns. Based on this I propose two testable hypotheses:

H1: Attention leads to short term increase in price.
H2: Attention leads to long term underperformance.

I test these hypotheses with Twitter data and try to show the value of Twitter as direct attention measure. As different methods can produce different results in different contexts, each combination of measure and scenario should be tested to find the combinations producing best, statistically significant values. This study focuses on measuring attention as tweets and using it in context of IPOs.

To test hypothesis H1, I regress first day returns on an attention measure, Abnormal Tweets Index (ATI), controlling for EBITDA, debt ratio, debt to equity, age of the firm, industry and current year to eliminate effect of IPO-heavy times. ATI has a statistically significant positive coefficient of 0.04416 with p-value of <0.1%. ATI has standard deviation of 1.0658 and an increase of one standard deviation equals to increase of 4.71% in first day returns. I also propose another attention measure, extra tweets (ET) which is directly measuring change in tweets while ATI is a relative measure. Doing the same regression with ET as I did with ATI, ET has coefficient of 0.0087 with near 0 p-value. Increase of one standard deviation in ET leads to increase of 10.1% in first day returns. Model with ET also has a significantly better fit than ATI.

Attention could also be result of investors expecting more from the IPO. This would make my H1 untrue. To verify that attention is not result of expectations I add a control variable for expected IPO returns. Even when considering the expected returns, ET has a significant positive effect on first day returns, rejecting the hypothesis that attention is result of expectations.

I test hypothesis H2 by creating abnormal returns for each IPO during the next year of trading and regressing those on ATI and ET controlling for the same variables as before. ATI has a non-significant negative effect on the abnormal returns, while ET has significant negative effect with p-value of <2%. To make sure that the negative abnormal returns are not result of large first day returns but the attention, I add first day returns as a control to the regression, which drops the significance of ET to p-value of 7.26%. This means that attention has significant predictive power on performance one year after IPO but increase in first day returns partly explains the underperformance.

2. Literature review

2.1 Attention

Kahneman (1973) goes through different aspects of attention from perspective of psychology. The capacity model of attention is most relevant to my study. It assumes there is a limit to man's capacity to perform mental work. This would mean that a single investor cannot pay attention to all stocks at once and can only focus on limited number of companies. Unless the investor chooses the stocks to trade at random, they should be paying attention to the security before making the investment decision. Investing requiring attention is the baseline of my study, as then more attention would imply more trades on stock.

Attention has been researched in the context of stock market before. Huberman and Regev (2001) found that only when attention is paid to news, it influences stock price. They saw an increase in price of a company after New York Times published an article of potential cancer-curing drug. This enthusiasm also affected the price of other biotechnology stocks. The thing was, Journal Nature and other newspapers had already reported the news five months earlier. Price hike happened only after general public paid attention on the subject. Attention has also been found to influence variance of returns and risk premia (Andrei, Hasler 2014) and under- and overreaction on earnings components (Hirshleifer et. al. 2011).

Barber and Odean (2007) say that human beings have bounded rationality, meaning we are limited to make our decisions by the amount of information we can hold and process simultaneously. Humans can make even complex rankings when there are only few alternatives, but when the number grows this becomes harder, even more so when the alternatives differ on multiple dimensions. To make the decision making more manageable, it is easier to limit the choice set. Odean (1999) proposes that as investors cannot "evaluate each security, investors are likely to consider purchasing securities to which their attention has been drawn". Measuring the changes on attention on a stock could therefore be used to predict increase in either demand or supply resulting in price movement.

Barber and Odean (2007) state that *"individual investors are net buyers of attention-grabbing stocks"* and that attention is *"a major factor determining the stocks individual investors buy, but not those they sell"*. They find that individuals do not really take short positions, and attention leads to increased demand while supply stays the same. Therefore "*attention-based purchases by many investors could temporarily inflate a stock's price, leading to disappointing subsequent returns"*. These findings would not apply to equally to institutional investors, as they put a lot more time into research and therefore have more attention available to different stocks and they do not differentiate that much between long and short positions. Findings of Barber and Odean support my hypotheses 1 and 2.

2.2 Measures

Different measures for attention have been proposed such as news (Schumaker and Chen, 2009), advertising expenses (Chemmanur and Yan, 2019), trading volume (Gervais et al., 2001) and extreme returns. These measures assume that attention should have been paid to stock because of increase in these factors and are therefore are only proxies for attention. Attention could also directly be measured by, for example, doing a questionnaire of what stocks investors thought about during the day consisting large number of participants, which is not cheap, viable or measurable afterwards. As a result, methods like Google search index has been proposed as direct measure attention. Choi and Varian (2012) show that Google Trends data can be used in "predicting the present", meaning it could be used to predict development of sales or economic indicators, but without the lag company or government reports have. Therefore, these attention measures could be used in real-time predicting. Da, Engelberg and Gao (2011) found that direct measure of attention, Google Trends had a significant predictive power on Russell 3000 stocks from 2004 to 2008 and did not correlate with previous measures of attention.

2.3 Twitter as predictor

Twitter has been used as a predictive tool in stock market context before. Bollen, Mao and Zeng (2011) found that mood from text content of daily Twitter feeds had 86.7% accuracy in predicting daily changes in closing value of Dow Jones Industrial Average and improved on previous models. Pagolu, Reddy, Panda and Majhi (2016) gathered Twitter sentiments on single companies and found a strong correlation with public opinion and price movements. Nofer and Hinz (2015) found no correlation between German tweets and stock market but when weighing in for the social aspect of platform, they created a trading strategy resulting in portfolio increasing 36% in six months after including transaction costs. Common theme in using Twitter as a predictive tool is sentiment analysis. Most studies have used Twitter with machine learning to find the current mood of the market and using the content of tweets in prediction. Some have used number of tweets like Oliveira, Cortez and Areal (2013) who found that number of tweets related to subject could be used in modelling the next day trading volume. I follow in their tracks and use number of tweets instead of the content to measure attention.

3. Data

Data was gathered primarily from open sources and is available for others to experiment with. IPO pricing data was gathered from Jay Ritter's IPO database and IPO Scoop data which also had the IPO rankings, IPO size was from Nasdaq and IPO activity, CRSP data on fundamentals and daily returns from Wharton Research Data Services (WRDS), SEC filings for SIC codes, and 3-factor model coefficients from Kenneth French's website. The Tweets were gathered directly from Twitter with a web scraper using the IPO date and ticker as variables.

The final merged dataset includes 976 IPOs from 22.1.2010 to 22.12.2017. IPO Scoop initially had 1427 IPOs for the same period but large amount of those were subtracted due to missing observations. Starting date is set by Twitter only showing Tweets from 2010 and ending date so that there were full annual returns and fundamentals for each company.

3.1 First day return

First day return of IPO is determined as seen in formula 1.

$$\frac{Stock\ price\ (end\ of\ first\ day)}{Offer\ price} - 1 = First\ day\ return \qquad (1)$$

Average first day return for the merged dataset is 15.1% (median 7.5%). The full IPO dataset for the same period from IPO Scoop had first day return with average of 12.1% (median 3.85%). The merged dataset used for regressions is different from full IPO dataset because some companies did not have all variables available for them. Reason is most likely the price over next year and survivorship bias, where IPOs that do not have full price data performed worse during IPO.

3.2 Abnormal return

To measure the abnormal return over the next year, I first get daily open and close stock data from CRSP. I do this to dates starting from IPO + 1 until IPO + 366, which is around 255 observations per stock. From this I calculate the daily stock return as (close/open-1). Next I merge these daily returns on Kenneth French daily factors for market return, small minus big, high minus low and risk-free rate. To get the abnormal return for each stock, I use the Fama-French three factor model and do the following regression (formula 2)

$$R_t - R_{ft} = \alpha_t + \beta\left(R_{Market\,t} - R_{ft}\right) + SMB_t + HML_t \qquad (2)$$

R_t	*= Return of stock on day t*
R_{ft}	*= Risk free return*
α	*= Daily abnormal return*
$R_{market} - R_{ft}$	*= Excess market return*
SMB_t	*= Size-factor*
HML_t	*= Value-factor*

Intercept of these regressions are the individual alphas for each stock, which I then use as a factor describing stock under- or overperformance over the next year.

3.3 Controls

As control variables I used EBITDA, debt to equity and debt ratio to control for the financials of the companies. These were acquired from Compustat annual fundamentals and either the year IPO happened or the next one, depending on availability. Other variables were age of the firm (IPO date – founding date), current year dummy to remove the effect of IPO heavy years, tech (SIC = 3559, 3576, 7389, 7371, 7379, 7372, 7373) and biotech (SIC = 2830, 2833, 2834, 2835, 2836, 8731) dummies to remove the effect of generally overhyped tech and biotech companies outperforming other IPOs.

3.4 Tweets and attention

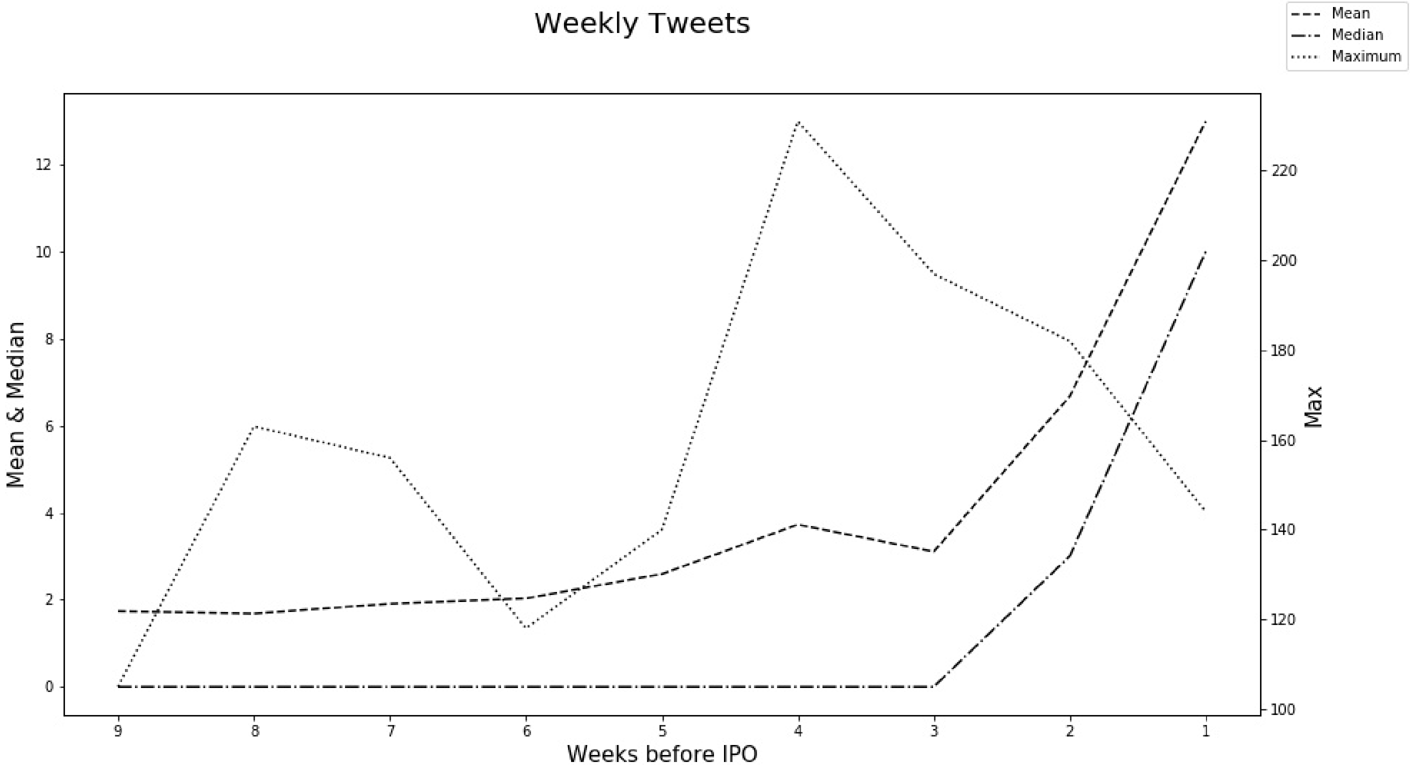
The microblog Twitter has 330 million active users worldwide in 2019. These users send over 500 million posts, or tweets, daily and around 200 billion tweets per year. Content of a tweet is free of form and only limited by Twitter's current character limit of 280. Twitter is a platform available to everyone and is used by both individual investors and those working as institutional investors. Tweets studied are mostly from individual investors because institutional investors are fewer in numbers and should not be sharing their trade secrets, so tweets by them are marginal. This is meaningful because individual and institutional investors behave differently, for example, institutional investors can be thought as more rational and unbiased, while individuals are more affected by biases.

I gathered the tweets directly from Twitter using a web scraper working with Twitter's own search function. The scraper counted tweets for each week from IPO date -1 to IPO date -63 so over the period of 9 weeks before the IPO date. I included all tweets that contained the ticker of a company and were in the corresponding timeframe. I used the ticker of company as search term because of the benefits and lack of downsides compared to other options. Ticker is unambiguous and either related to the stock directly, whereas the name of company can be associated with their consumer business, news or even something unrelated. None of those are attention to the stock and therefore useless. Company name is also longer which does decrease number of totally unrelated tweets in the search but increases the chance of misspelling and decreases sample size. Downside of ticker is that it is usually not known before IPO announcement. Based on the data I assume ticker is usually announced between 4 to 5 weeks before the IPO date and therefore tweets on weeks before that should not be associated with the company and are just noise. Figure I plots the distribution of tweets.

Figure I.

Descriptive graph of number of tweets.

Weekly average and median of tweets on left, and the most tweets company has received on the right. X-axis represents how many weeks before IPO. Number of tweets on ticker has a clear increase when IPO date approaches, even though weekly median goes above zero only two weeks before IPO. Median is constantly below average, because some values are significantly larger as seen by highest number of tweets.



The number of tweets gathered has some variation which I cannot remove. As Tweets were gathered with a web scraper directly from Twitter and no manual selection was done, the amount depends somewhat on Twitter and what it decides to show. Therefore, the numbers can be different over different searches. This issue could be tackled in future studies by buying Twitter's premium API which allows direct search from Twitter's archive without requiring to see the Tweets. I did not use this method because it is expensive.

I calculated each tweet as "one attention" and no differentiation was done based on the content. For example, someone might be tweeting how they like the name of CEO of the firm while other user might tweet a link to in depth research on the IPO and these both would be treated equally. In future studies, content of tweets could be considered by increasing their weight if the information was deemed more valuable. Social factor should also be considered, for example, how many retweets (shares) tweet received.

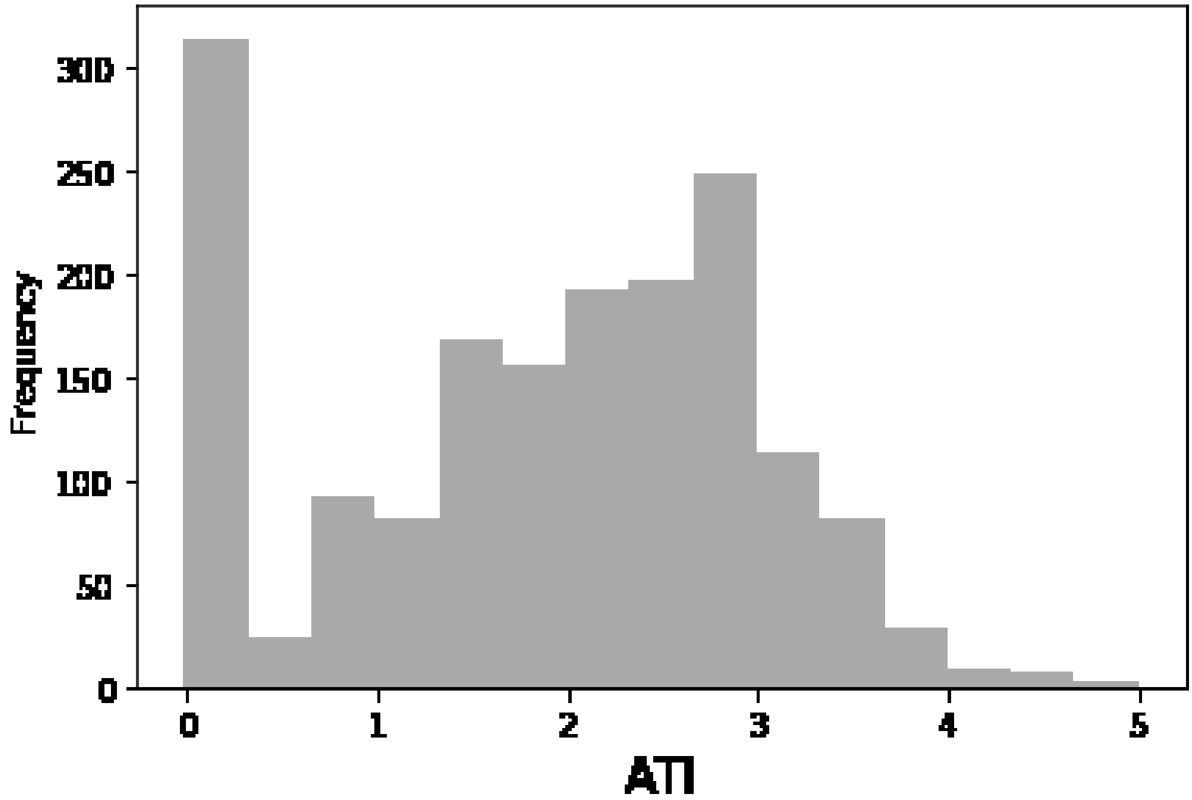
For the regression I use abnormal Tweets Index (ATI). I calculate ATI for week t in formula 3:

$$ATI\ (t) = Log(tweets(t)/(median\ (tweets(t-1)\ to\ tweets(9))) \tag{3}$$

ATI is comparing tweets of week (t) to median of tweets from previous weeks. I also calculated ATI for 8 weeks before IPO to find if the effect of attention from previous weeks has significance on IPO performance. I adjust both tweets (t) and the median so that if the value is 0, I changed it to 1. This is done to increase the amount of valid observations as zero in either numerator or denominator results in a non-valid result. Figure II shows a histogram of ATIs.

Figure II.
Descriptive histogram of ATI of one week before IPO.

Histogram showing ATI distribution with overflow baskets for negative values and values over 5. To note is the spike in second column, which is from the large number of 0's in the data. They are mostly a result from 0 tweets during previous weeks and current week, which after the adjustment is Log (1/1) = 0



I use this method to calculate the ATI because relating tweets to previous weeks controls for the conspicuousness of the company. The previous weeks determine a baseline of how many tweets the ticker has, noise included, and ATI determines the increase compared to that. A more well-known company like Facebook will have more attention compared to less-known companies and tickers like $NETS or $WOW have more noise because of the ambiguousness. Logarithm is used so the values are closer to normal distribution. I also propose another method of measuring attention called Extra Tweets (ET). I define ET for week t as follows:

$$ET\ (t) = tweets(t) - (median\ (tweets(t-1)\ to\ tweets(9)) \qquad (4)$$

ET differs from ATI as it is an absolute measurement of change whereas ATI is relative. Both compare tweets of week (t) to previous weeks and seem to have a merit to them, so I test the effect of both.

4. Methods and results

4.1 Abnormal tweets index

Table I.
Effect of individual ATIs on first day returns.
First day return ~ ATI (week (t)) + EBITDA + D/E + debt ratio + age + industry + year

	ATI coefficient	P-value	Significance
Week -1	4.42E-02	9.51E-06	***
Week -2	3.99E-02	1.15E-04	***
Week -3	3.50E-02	6.17E-03	***
Week -4	5.52E-02	1.05E-06	***
Week -5	5.66E-03	6.54E-01	
Week -6	1.08E-02	4.80E-01	
Week -7	-1.07E-02	5.20E-01	
Week -8	-3.02E-02	1.38E-01	

Table I shows the results of all ATIs of first day return regressed on ATIs of individual weeks and control variables. Weeks one to four before IPO all have ATIs that are statistically significant and have positive effect on the first day returns while weeks five to eight are not significant. Somewhat surprisingly these coefficients and p-values show that ATI of 4 weeks before IPO has the largest and most significant positive effect on IPO price, the coefficient being even larger than one week before IPO. This could be explained in the way ATI is calculated. ATI of one week before IPO is comparison of week -1 to median of weeks -2 to -9, while ATI week -4 is compared to median of weeks -5 to -9. As weeks -2 to -4 seem to have more tweets, the value that week -1 is compared to should be higher than what week -4 is compared to leading to smaller ATI for week -1. Change of one standard deviation in week -1 would lead to change of 4.71% in first day returns. Change of one standard deviation in week -4 would be 4.50% in first day returns.

The regression makes it look like the weeks -1 to -4 might all have significance on IPO first day returns and 4 weeks before IPO would have the most significant effect. It could also be that the ATIs are highly correlated with each other and therefore weeks -1 to -4 all seem to have a positive effect. Table II shows correlation matrix between ATIs

Table II.

Correlation matrix for ATIs.

Correlation between the ATI of week on Y-axis and week on X-axis.

	1	2	3	4	5	6	7
2	0.58						
3	0.27	0.34					
4	0.30	0.32	0.37				
5	0.16	0.19	0.13	0.13			
6	0.06	0.07	0.05	-0.01	0.13		
7	0.03	0.07	0.12	-0.02	0.10	0.11	
8	-0.02	-0.01	-0.01	0.00	-0.01	-0.04	0.01

Correlation matrix indeed shows high correlations weeks 1,2, 3 and 4 have with each other. It also shows that weeks with longer time between each other have smaller correlation. This is expected, as attention lingers for some time (Kahneman ,1973) so week after attention spike should still have some remaining because the news leading to attention spike is still relevant and new people are just finding out about it.

Weeks -7 and -8 have little correlation with other weeks, which could be explained because there is no real abnormal attention going on yet. Either the IPO has not yet been announced or it is so far away that no real attention is paid to it. This might also explain why week 4 has high correlation with week's 1-3 and low with 6-8 as that might be the aggregate announcement time of IPO, where attention is starting to grow.

Table III.
Effect of all ATIs on first day returns

First day return ~ ATI (1) +ATI (2) +ATI (2) +ATI (3) +ATI (4) +ATI (5) +ATI (6) +ATI (7) + controls

	Coefficient	P-value	Significance
ATI week -1	0.02872	9.36E-03	**
ATI week -2	0.0174	1.37E-01	
ATI week -3	0.008906	5.14E-01	
ATI week -4	0.04332	2.93E-04	***
ATI week -5	-0.005173	6.83E-01	
ATI week -6	0.01354	3.75E-01	
ATI week -7	0.01306	4.32E-01	

Table III shows the regression results of first day returns on ATIs of weeks -1 to -8. The regression states that ATI of the week just before IPO and 4 weeks before IPO have a statistically significant positive effect on first day returns. Surprisingly the ATI of 4 weeks before IPO has even larger effect on first day returns than one week before. This is somewhat negated when considering the standard deviation, change of one standard deviation in ATI of week -1 is 1.066 and week -4 is 0.8161 so change of one standard deviation equals change of 3.06% and 3.54% in first day returns.

The significance of week -4 would imply that something happens 4 weeks before the IPO and it would support the idea from correlations that week 4 is the aggregate timing for ticker release or IPO announcement and is the first attention spike. Other things to note from the regression are that week's 2 and 3 had a statistically significant positive effect in individual ATI regressions but now they seem to have little to no significance. This is most likely because the high correlation they have with weeks 1 and 4

4.2 Other attention measures

I used ATI as a primary measure of attention based on the research of Da, Engelberg and Gao (2011), where they used abnormal search volume index (ASVI) created with the same formula I used for ATI but from Google Trends data. For them, an absolute change does not really make sense as data in Google Trends is already an index (day with most searches has value of 100 and other days are compared to that). For me, an absolute measure is also a viable option, as the weekly tweets are absolute numbers. Next I replicate the regressions I did with ATIs with an excess tweets (ET) to compare significance. Results are shown in table IV.

Table IV.
Effects of individual ETs and all ETs
Individually = First day return ~ ET (t) + controls
Together = First day return ~ ET(1) + ET(2) + ET (3) + ET (4) + ET (5) + ET (6) + ET (7) +ET(8) + controls

	Each ET individually			Each ET in same regression		
	ET coefficient	P-value	Significance	Coefficient	P-value	Significance
Week -1	8.79E-03	1.97E-25	***	8.83E-03	0.00	***
Week -2	5.15E-03	5.00E-07	***	-9.29E-04	4.81E-01	
Week -3	1.46E-03	2.85E-01		-2.42E-03	1.18E-01	
Week -4	4.25E-03	5.17E-05	***	3.12E-03	1.45E-02	*
Week -5	1.80E-03	1.40E-01		7.04E-04	6.14E-01	
Week -6	1.21E-03	4.57E-01		-4.09E-04	8.04E-01	
Week -7	-6.41E-04	6.53E-01		-8.69E-04	5.63E-01	
Week -8	-7.04E-04	7.63E-01		-1.61E-04	9.45E-01	

Weeks 1, 2 and 4 have significance by themselves, while weeks 1 and 4 have significance in regression where each ET is present. This is very similar to previous results from using ATI. Standard deviation of ET one week before IPO is 11.5, so a change of one standard deviation would lead to a change of 10.15% in IPO first day returns. The model with all ETs has a better fit than the one with all ATIs (adjusted R-squared 0.15 > 0.075) which might make it even preferable to using ATIs. Both measurements, the ATI and ET, have statistically significant predictive power to IPO first day returns.

Table V.
All attention measures in one regression.
First day returns ~ ATI (1) +ATI (2) +ATI (2) +ATI (3) +ATI (4) +ATI (5) +ATI (6) +ATI (7) + ET (1) + ET (2) + ET (3) + ET (4) + ET (5) + ET (6) + ET (7) + controls

	Coefficient	P-value	Significance
ATI week-1	-3.71E-02	1.01E-02	*
ATI week-2	1.55E-02	3.02E-01	
ATI week-3	8.66E-03	5.70E-01	
ATI week-4	1.51E-02	3.04E-01	
ATI week-5	-1.64E-02	3.06E-01	
ATI week-6	1.43E-02	4.36E-01	
ATI week-7	-1.49E-02	4.04E-01	
ET week -1	1.10E-02	0.00E+00	***
ET week -2	-2.86E-03	1.13E-01	
ET week -3	-2.69E-03	1.35E-01	
ET week -4	1.68E-03	2.99E-01	
ET week -5	2.05E-03	2.67E-01	
ET week -6	-1.66E-03	4.22E-01	
ET week -7	4.56E-05	9.79E-01	

Results of combining all ATIs and ETs into a single regression are in table V. All other weeks but the one before IPO lose their significance. Coefficient of ATI of week-1 turns negative, while ET of week -1 keeps the positive sign. This would imply that using ET of week -1 as an explanatory variable would be the best when trying to predict IPO returns with Twitter.

I have some gripe with using only the ET. In a situation where median is 10 and week (t) is 15 the ET is 5 while ATI is 0.41. When these numbers are 55 and 60 ET is still 5 while ATI goes down to 0.08. ATI is a relative measurement and clearly shows the situations are different while ET does not do that. Both do show a significant effect on first day returns, but as ATI and ET of the same weeks have a correlation of around 0.6, so including both in one model might not be useful. Table IV and V also show that using ATI and ET of week -4 might also have some predictive power, so I will also use those.

4.3 Returns over the next year

If the upward price movement is based on the increased attention stock receives and not the fundamentals, efficient markets should eventually bring the trading price back to intrinsic value. This would mean that the large first day return based on attention would be temporary, and the price would decrease after that, meaning that stock would have negative returns compared to market during the next year.

To measure the next year excess returns, I use 3-factor model and regress daily stock returns on daily 3-factor coefficients, the excess market returns, small minus big (SMB), and high minus low (HML) (equation 2). I do this to each individual IPO and as a result of these individual regressions are the alphas which describe the daily under- or overperformance stock has compared to market, or the abnormal returns. Median of the abnormal returns over the next year is -2% so IPOs have underperformed the market. To see if pre-IPO attention affects the returns stocks have during year after IPO, I regress the alphas I got from 3-factor model on ATI and ET with both individually and together controlling for the usual variables. Below in table VI is the summary of those regressions.

Table VI.
Best attention measures on one-year excess returns.
Individually = Abnormal returns ~ ATI (-1) or ET (-1) + controls
Together = Abnormal returns ~ ATI (-1) + ET (-1) + controls
Regressing annual abnormal returns on best attention measures from table VI.

	Individually			Together		
	Coefficient	P-value	Significance	Coefficient	P-value	Significance
ATI week-1	-0.004458	6.61E-01		0.0147	0.24077	
ET week-1	-0.002068	1.85E-02	*	-0.002817	0.0095	**

I

n both regressions ATI has a statistically insignificant effect, negative when alone and positive with ET. This implies that ATI has no real power in predicting the abnormal returns year after IPO. ET has a statistically significant negative effect on abnormal returns stock experiences on the year after IPO both alone and with ATI. This would imply that large attention increases to the first week before IPO leads to a decrease in returns during the next year supporting the hypothesis that stocks perform worse during the year after IPO partly because the attention, at least when attention is measured with ET. When used in the regression alone, change of one standard deviation in ET (11.5) means a decrease of 0.024 in abnormal returns. The abnormal returns are daily values and therefore to get more understandable figure like annual abnormal returns, the value must be multiplied by number of trading days, which is around 255 days. In the regression table, the values are also expressed as 100 times larger to make them more sensible. Therefore, increase of one standard deviation in ET equals leads to abnormal annual returns of -6.12% (0.024/100 * 255)-

Intercept in table VII models are significantly negative, meaning that not all of IPOs underperformance during the year after IPO is explained by attention. This underperformance could be result of large first day returns. As investors find their IPO has overperformed expectations, they might start selling off their position. They could have also just taken part to the IPO to benefit from the generally present IPO under-pricing (Ritter and Welch, 2002). Either way, because of the sell-off after IPO, both scenarios would imply that stock price decreases after the first day of IPO. To test if the excess returns during the next year are lower because of larger first day returns and not the attention, I regress the excess returns on both attention measures and add a control for first day returns to eliminate its effect in table VII.

Table VII.
Effect of attention on abnormal returns during next 52 weeks controlling for first day return.
Abnormal returns ~ ATI (-1) + ET (-1) + first day return + controls.

	Coefficient	P-value	Significance
ATI week-1	0.01285	3.05E-01	
ET week-1	-0.002045	7.26E-02	.
First day return	-0.07721	2.83E-02	*

This regression decreases the significance of ET and it cannot be said to have a statistically significant effect at 5% confidence. It still has p-value of 0.0726, so it cannot be said that all the negative abnormal returns during year after IPO are results from high first day returns. It does not reject my hypothesis 2 but it does not confirm it either.

4.4 Interpretation and counterpoint

Attention measured with ATI has positive significant effect on first day returns. Measured with ET, it has a positive effect on first day returns and a negative effect on abnormal returns for a year after IPO first day close. These follow my initial hypothesis that attention leads to upward price pressure which initially increases prices but makes them go down in the long run as fundamentals and more rational investors start playing a larger role.

There is also a chance that the first day returns are not happening because of the attention, but that investors give a company attention because they expect it to be under-priced and therefore have larger first day returns. As Choi and Varian (2012) said about Google Trends, *"We are not claiming that Google Trends data can help in predicting the future. Rather we are claiming that Google Trends may help in predicting the present"*. Their research showed that Google Trends data could be used in forecasting economic indicators like unemployment claims or consumer confidence. This could also be the case in my study, that maybe the attention is not really the factor driving up first day returns and is only result of higher expectations.

IPO Scoop, where I also got the stock return data, is an independent research firm. The IPO data also includes their ranking on how IPOs are expected to perform. They rank IPOs from 1 to 5 stars on how much first day returns it is expected to produce. They have accuracy of 89% over 19-year period, so the ratings are very reliable predictors on expected IPO performance. Adding the rating data to my models should control for the higher expected returns and leave just the effect of attention on first day returns in table VIII.

Table VIII.
Effect of attention on first day returns controlling for expectations.
First day return ~ ATI (-1) + ET (-1) + rating + controls

	Coefficient	P-value	Significance
ET week-1	0.007189	1.94E-13	***
ATI week-1	-0.01909	8.06E-02	.
Rating	0.1057	0.00	***

IPO Scoop ratings had a very significant predictive power on IPO returns, but ET of first week before IPO had almost as much significance. This would imply that even when controlling for expected returns attention has a significant positive effect when measured with ET.

Table IX.
Effect of attention on abnormal returns during next 52 weeks controlling for expectations and first day returns.
Abnormal returns ~ ATI (-1) + ET (-1) + rating + first day return + controls.

	Coefficient	P-value	Significance
ATI week-1	0.0126	3.19E-01	
ET week-1	-0.002263	4.87E-02	*
Rating	0.01472	0.21	
First day return	-0.09338	1.44E-02	*

Table IV regresses abnormal returns controlling for both rating and first day returns. It shows that first day return expectations have no significance on abnormal returns during the year after IPO and controlling for them further increases the significance of attention to statistically significant levels. The possibility of attention being result of expected returns is still there, but evidence would say otherwise. This would also mean that the hypothesis that negative abnormal returns are a result of investors selling of after looking for the IPO profit is not true, because expectations do not influence abnormal returns. Based on this, my hypothesis that attention leads to positive first day returns and eventual negative returns seems to be strongly supported.

5. Real world applications

To take part in IPO and get the shares at offer price, investor must be on the move some weeks before the IPO. That is earlier than this method allows, as you must gather data from entire week before IPO, which you only have on the IPO date. Therefore, comparing tweets from pre-IPO week to previous 8 weeks is not feasible as investor cannot enter the position at the offer price. With that in mind, I propose two different investment strategies that utilize Twitter data in IPO context.

First strategy is where investor gathers all the data required to replicate ATI or ET, and enters the IPO based on those at the price where trading opens at. This investor misses the initial returns (opening price/offer price -1), which averaged 13.8% with median of 7.3% over the sample. Second strategy I try is to use the earlier ATIs and ETs creating a strategy based on those, which allows investor to enter at opening price. I compare these strategies to taking part in all IPOs indiscriminately to find if there are excess returns to be made.

To see if the first strategy might be viable, I first regress the first day returns since open, those returns available if investor did not put money to IPO but got the shares at the start of trading, controlling for the IPO variables. This gives the regression table X.

Table X.
Effect of attention on first day returns since opening price
First day returns since open ~ ATI (-1) or ET (-1) + controls

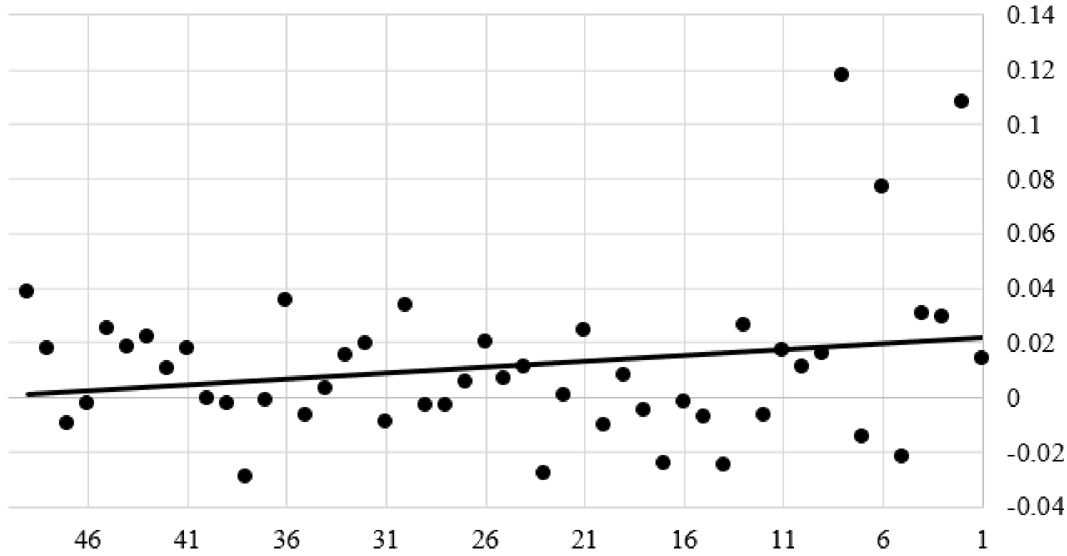
	Coefficient	P-value	Significance
ATI week-1	-0.004804	0.40	
ET week-1	0.0009842	4.57E-02	*

Only ET has a statistically significant positive effect on first day returns since open. Therefore, I use it instead of ATI for the strategy. To see what kind of returns ET could produce, I split it into groups of 20 stocks. Figure V shows the graphical split of those groups.

Figure V.

Portfolios ranked by ET

Portfolios containing 20 stocks ranked by their ET of one week before IPO. Rank 1 has stocks with 20 largest ETs and rank 49 has the stocks with lowest ET. Y-axis has the average first day return of each portfolio since open of trading.



ET seems to have somewhat positive effect. all groups that averaged over 4% returns since open are in the top 10 by ET and the trendline has a positive slope. Still, there are negative and close to zero averages even at ranks above 40. Setting certain limit on ET to make a clear strategy would yield results in table XI.

Table XI.
Average returns

Average first day returns since open for stocks above certain ET ranking, and how many IPOs fill that criteria during the time period.

ET	Average returns	Number of IPOs
> 50	-0.08%	14
> 30	4.87%	57
> 20	2.75%	150
> 10	1.46%	468

As returns for first day since open averaged 1.1%, excess return of 1.65% is available in this dataset when using ET of > 20. This is only for 150 IPOs over the period of 8 years, so available returns are limited by the number of IPOs. Also, the returns missed by buying the stock at opening price instead of the offer price a very significant. Missing the initial price jump therefore does not seem worth it just to get data with larger predictive power.

Another possible strategy I propose is using the ATIs or ET of earlier weeks like 4 or 5 weeks before IPO. At those timings the investor, at least institutional one, should be able to enter the IPO at relatively little costs.

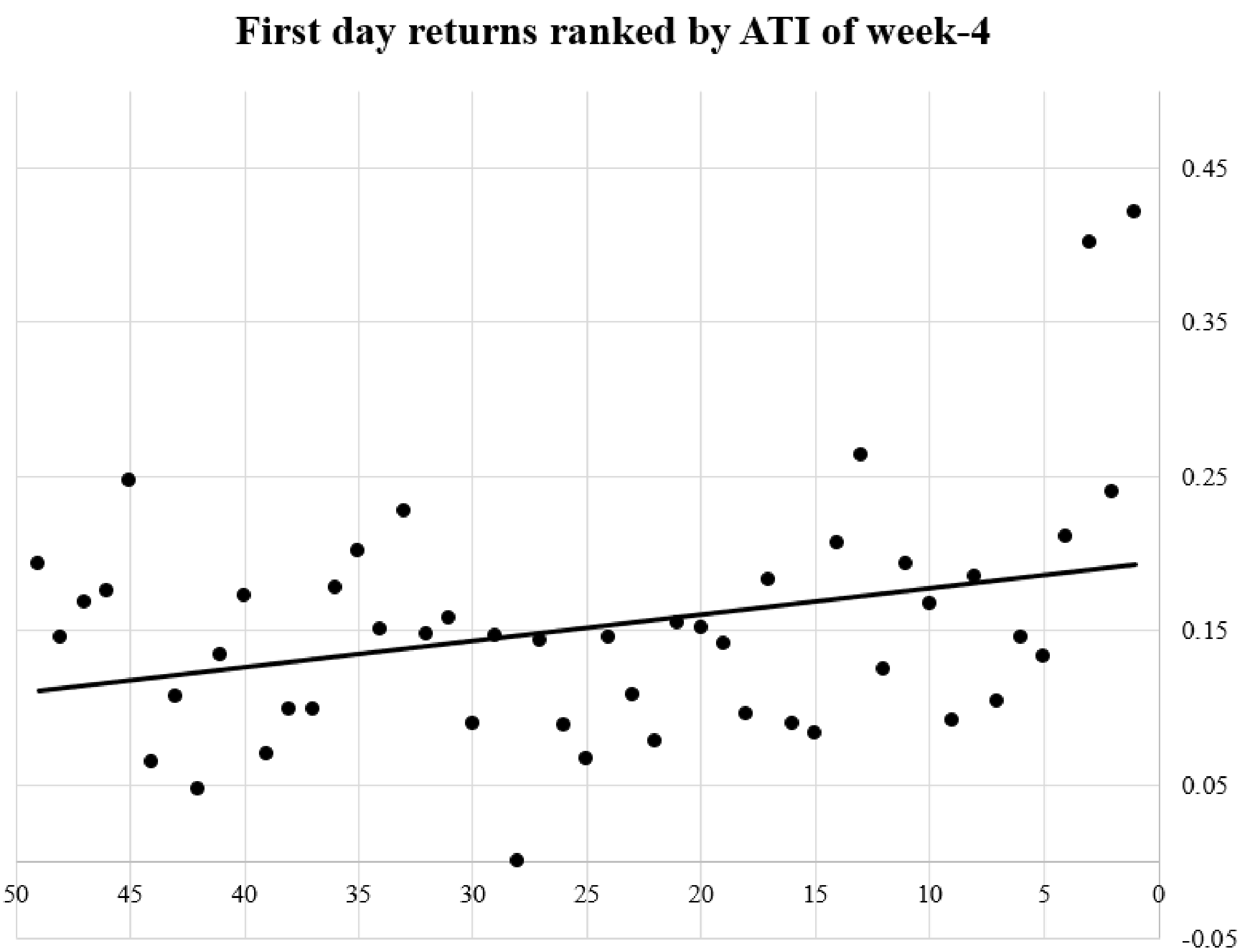
As first day returns averaged 15.1% over the period, that is the benchmark I try to beat with this strategy. Table XII shows the best predictive measure for the earlier weeks.

Table XII.
Best measure for attention excluding one week before IPO
First day returns ~ ATI (2) +ATI +ATI (3) +ATI (4) +ATI (5) +ATI (6) +ATI (7) + ET (2) + ET (3) + ET (4) + ET (5) + ET (6) + ET (7) + controls

	Coefficient	P-value	Significance
ATI week-2	0.006237	0.66	
ATI week-3	0.01777	2.60E-01	
ATI week-4	0.03128	3.99E-02	*
ATI week-5	-0.004218	0.80	
ATI week-6	0.006603	0.73	
ATI week-7	-0.008999	0.63	
ET week-2	0.004202	0.01	**
ET week-3	-0.002916	0.12	
ET week-4	0.002401	0.15	
ET week-5	-0.0009103	0.63	
ET week-6	0.001108	0.60	
ET week-7	-0.001543	0.39	

The strongest positive effect on first day returns was shown by ET of 2 weeks before IPO but I deem it too late and use the next strongest predictor, ATI of week -4. This data is available 3 weeks before the IPO date which would allow at least institutional investors to still take part in the IPO at offer price. Figure VI is the same figure as figure V but with ATI (-4) and returns from offer instead of open.

Figure VI.
Portfolios ranked by ATI of week -4
Portfolios containing 20 stocks ranked by their ATI of four weeks before IPO. Rank 1 has stocks with 20 largest ATIs and rank 49 has the stocks with lowest ATIs. Y-axis has the average first day return of each portfolio from offer price.



In figure VI there seems to be more of a trend going on. Increase of ten ranks in ATI would imply 1.9% increase in first day returns. From this, getting the above the average 15.1% returns would mean going for IPOs above rank 26 (0.0019x + 0.1017 => 0.151 → x => 26) or about top 400 IPOs. This is problematic because at 4 weeks before IPO, the ATIs are relatively small and at rank 26 the ATI is already 0. Also, using strategy based on ranks does not give a clear-cut value when investors should invest, because IPO ranking depends on the dataset they are compared to. To get a clear value of ATI above which the investment should be done, I use the same sorted values and calculate the averages above certain thresholds. Just maximising average returns is not the correct way to go, because this would significantly decrease the total returns available, even though the average might be better.

Table XIII table has the average returns over certain ATI and the excess returns those would produce. Excess returns are the returns above average of 15.1% so average returns (ATI) – 15.1%. Next is the number of IPOs filling the ATI criteria. I use total returns and total excess returns to factor in the amount of IPOs investor could have partaken during this period by following the ATI limit.

Table XIII.
Average returns above ATI threshold.
Average first day returns since offer for stocks above certain ATI ranking, how much that is compared to average, how many IPOs fill that criteria during the time period and how much total returns investment of 1 in each of the IPOs would return.

ATI	Average returns	Excess returns	Number of IPOs	Total returns
> 3	52.7%	37.6%	11	5.8
> 2.5	44.7%	29.6%	23	10.3
> 2	36.3%	21.2%	51	18.5
> 1.5	26.0%	10.8%	122	31.7
> 1	20.9%	5.8%	201	42.0
> 0.5	20.4%	5.3%	268	54.7
> 0	19.8%	4.6%	300	59.3
>= 0	15.0%	-0.1%	924	138.7
< 0	17.5%	2.4%	52	9.1
All	15.1%	0.0%	976	147.8

As ATI decreases, average returns decrease significantly. Investing in those IPOs with ATI of over 3 would yield average returns of 52.7% per IPO but the problem is with the number of IPO filling the criteria. Over the period of 22.1.2010 to 31.12.2017 only 11 IPOs have had ATI of over 3 in the week 4 before IPO. That is less than 2 every year, so going for the largest average returns has only limited upside.

Total returns available is how much investor could make by investing equally on each criterion matching IPO (average returns * number of IPOs). This is to demonstrate what investor is missing out on if they limit themselves to certain IPOs and pass those with small ATIs. Limiting the selection of IPOs only makes sense if there are some costs associated in investing in more IPOs. It could reasonably be assumed that there are some, as at least individual investors must pay the money upfront some weeks before IPO. During that time the money is not producing any returns and therefore the are at least opportunity costs.

Limiting the IPOs in which to partake by ATI does increase the available excess returns but also decreases available total profits. Therefore, picking IPOs based on ATI should only be done if available funds are limited. To increase average returns without decreasing total returns investors could use ATI as a weighing factor. For example, instead of investing 1 on each IPO, investing with the factor of ATI value on each IPO with ATI over 0. In the data this would mean investments on exactly 300 IPOs with weighted returns of 23.7%. Returns from investing on these IPOs with equal weighing is only 19.8% meaning ATI weighting produces first day excess returns of 3.96% in this dataset.

Strategy is not fool proof as some IPOs are heavily oversubscribed and investors do not receive all the shares they signed up to buy, but are allocated only a portion of those (usually x + percentage amount of total asked). This might result in problems with the strategy, as if investors realize that issue is under-priced, oversubscription is more significant (Chowdhry and Sherman 1996). I did not verify the strategy with allocation amounts, which most likely will eat some of the excess returns.

6. Conclusion

As investments should not be done without paying attention on the company, measuring the amount of attention on stocks could help in predicting price movements. I study the value of Twitter as an attention measurement and effect of that attention on initial public offering first day returns and abnormal returns during the next year.

I create two hypotheses based on existing literature: attention increases the first day returns and attention decreases the abnormal returns during the next year. I propose two different measures of Twitter attention, abnormal tweets index (ATI) and extra tweets (ET) and find that both are valuable measurements, but ET proves to be the better option. Measured with ET attention does have a positive significant effect on first day returns and negative significant effect on abnormal returns during next year, supporting both my hypotheses.

It could be that attention is not the reason for increased first day returns but attention is results of expectations of larger first day returns. When the effect of expectations is eliminated, ET still has a significant positive effect, meaning attention should not be based on purely on expectations.

I test IPO trading strategies and find that investor can increase their first day returns by either trading stocks at open based on ET of one week before IPO or taking part in IPOs by using ATI of four weeks before IPO as a weighting factor. This creates excess first day returns of 1.65% and 3.96%. respectively. It still might not make sense for investors to skip out on some IPOs because the returns have been very high even on average. Picking the best IPOs also leads to problems with hot IPOs, where investor does not receive all shares, but they are allocated some part of the original ask. Because of that, picking IPOs which to partake in based on ATI is mostly recommended for individual investors.

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